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Human Capital Accumulation and Spatial TFP Interdependence

*Tapas Mishra & Mamata Parhi & Claude Diebolt**

Abstract: »*Human Kapital Akkumulation und Räumliche TFP Interdependenz*«. This article provides evidence of cross-country total factor productivity (TFP) interdependence due to human capital accumulation over time by employing a semi-parametric spatial vector autoregressive technique in the panel. Empirical study covers a set of 15 Asian countries over the time period 1970-2000.

Keywords: total factor productivity, spatial growth, human capital, semi-parametric panel VAR, cliometrics.

1. Introduction

The importance of total factor productivity (TFP) growth to economic growth variation in a single country setting can be dated back to as early as Solow¹ (1956). Traditionally, TFP is defined as the portion of output not explained by the amount of inputs used in the production. The ‘residual’ (often termed as Solow residual) has been shown in numerous studies to contribute extensively to the growth (variations) by way of strong correlation with output and hours worked. The underlying empirical artifact lies at the core of the real business cycle theory (see for instance, Kydland and Prescott, 1982). Notably, the most important term of TFP, the productivity, has multidimensional and complex connotations; improvement of efficiency of input use in production being one of them. Higher efficiency gain in input use in production determines the level of TFP as ‘residual’. In the standard business cycle model, shocks to TFP are propagated by pro-cyclical labor supply and investment, thereby generating fluctuations in output and labor productivity at business cycle frequencies. So far, the extant empirical verifications on the correlatedness of TFP growth, business cycle and technological changes have been limited to individual country setting. Some recent studies (in addition to Solow, 1956), which are not

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¹ In his landmark article, Solow (1956) shows that long-run growth in income per capita in an economy with an aggregate neoclassical production function must be driven by growth in TFP.

‘spatial’ *strictu sensu*, however demonstrate that cross-country differences in technology may generate cross-country differences in income per capita. Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999), for instance have confirmed that a majority of the gap in income per capita between rich and poor countries is associated to large cross-country differences in TFP. The foremost cause of the cross-country differences as laid in these studies is due to differences in the physical technology used by countries or in the efficiency with which technologies are used.

It may be noted that the studies described as above point at an *ad hoc* measure of cross-country differences in TFP, and do not reflect *per se* the measure and consequences of correlatedness across countries and over time. One cannot gather information, therefore on source of cross-country correlation of TFP over time. It was also not possible to know if the possible TFP interdependence was due to changing patterns of human capital accumulation in different countries. The probability that TFP (level or growth) is correlated across spatial locations can be supported by the following fact. It is known that despite the preserved identities of national economies in the geographical space, recent years have witnessed rapidly shrinking of socio-economic borders. This arguably makes countries’ production processes correlated through knowledge spillovers, and technological exchanges via foreign direct investment – in summary through tradeable and non-tradeable goods and services. Geographical borders continue to lose its significance in the face of rising relational proximity. Moreover, adjacent countries (sharing the common borders and others interconnected through this linkage) are more likely to be affected by relational change occurring at any one of them. Additionally, commonality of socio-economic and demographic attributes of differential degrees is yet another reason to premise why countries’ TFP (growth and/or level) could be interrelated over time and across space. A natural question that arises in this context is to understand ‘what contributes to this *interconnectedness* which is common to all these countries’?

A plausible explanation can be invoked with respect to the commonality of type and speed of demographic change in different regions around the world. The way country blocks (say Africa, Asia and Europe) grow in population age and age-structured human capital can be different. Take for instance, the rate of growth of population having secondary or more education in the 15-29 age group. Understandably, the rates differ substantially between Asia and Europe but may find similar patterns within the respective regions. Since educational status by age-groups reflects the productivity level of population and possibly the availability of the number of working hours, the production process as well as the productivity (TFP) in these regions would be substantially different. However, countries within Asia and Europe may share similar trends due to the fact that their economies share common structural parameters (*viz.*, social, demographic and to some extent economic). Taking this plausible commonality

route, it is possible to explain the existence of spatial interdependence of TFP among these countries which provides a cliometric explanation of cross country productivity variations.

The present paper attempts to reflect on the above question by studying interdependence of TFP among countries with respect to cross-country human capital dynamics using the novel approach of semi-parametric spatial vector autoregressive framework for panel data (see Chen and Conley, 2001; Azomahou, Mishra and Diebolt, [in press]). The questions that we seek to answer are the followings: Do geographically-clustered countries share common cyclical features? How does one model the interdependence of TFP among countries given that feedback effect occurs from technological changes to efficiency of input appropriation in the individual country and that the country's growth is correlated over time and over different spatial locations? To address these questions, we argue in this paper that locational growth dynamics of human capital can explain the spatial interdependence of TFP. From a cliometric perspective, application of this new technique to TFP co-movement has many interesting implications – important among them being the spatial correlatedness of business cycles and the common mechanism generating this feature over decades. To carry our argument and illustration further, in section 2, we discuss theoretical and empirical specification of our proposed model. In section 3, we present the empirical results and provide discussion of the results. Section 4 concludes with main implications of the study.

2. Model

2.1. Theoretical specification

Being an important input in the modern growth theoretic production technology, human capital substantially accounts for the generation of total factor productivity (Benhabib and Spiegel, 1994, 2005). Indeed, TFP and human capital have more discernible association than any other inputs of production. Human capital adds efficiency value to labor input and combined with productive labor, also contributes directly to the generation of physical capital. Consider, for example, a Cobb-Douglas production function exhibiting constant return to scale and decreasing returns in each factor in the following specification:

$$Y_{it} = A_{it} K_{it}^{\alpha} H_{it}^{\gamma} L_{it}^{1-\gamma} \quad \dots \quad \text{Eq. 1}$$

The TFP is described in Eq. 1 by the parameter A which evolves according to

$$\frac{\dot{A}_t}{A_t} = \Omega k_t^{\alpha}.$$

A simple representation of TFP where human capital is a factor of production is given (as in Nelson and Phelps, 1966) as:

$$\frac{\dot{A}(t)}{A(t)} = f(H_i(t)) + v(H_i(t)) \left(\frac{A_m(t)}{A_i(t)} - 1 \right) \quad \dots \quad \text{Eq. 2}$$

Where $A_i(t)$ is the TFP of country i at period t , $f(H_i(t))$ is the component of TFP growth that depends on level of education – here the human capital in country i and

$$\left(\frac{A_m(t)}{A_i(t)} - 1 \right)$$

is the rate of technology diffusion from the leader country m to country i . The last term of Eq. 2 can be replaced by a term,

$$H_j^\xi(t)$$

describing international transmission effects of productivity or knowledge. The power ξ in this term reflects the speed at which knowledge transfer occurs from country j to i . This basic formulation lies at the heart of estimating a spatial spillover model of TFP with human capital. Key properties of this model are presented in the next section.

2.2. Econometric specification: Semi-parametric spatial VAR

We describe dynamics of TFP co-movement in a semiparametric spatial vector autoregression (VAR) framework. The specification concerns a panel vector autoregressive model of TFP growth rates where the dynamical relationship in the model is upheld by correlation in the human capital accumulation and where the structure of the error term allows for a general type of spatial correlation across countries. The econometric specification and the estimation method used are based on an extended framework of Chen and Conley (2001) and Conley and Dupor (2003) and is closely linked to Azomahou, Diebolt and Mishra (in press).

The model is described by:

$$V_{t+1} = A(D_t)V_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} = Q(D_t)u_{t+1} \quad \dots \quad \text{Eq. 3}$$

Where

$$V_t = (Y_{1,t}, Y_{2,t}, \dots, Y_{N,t})' \in R^N$$

is a vector stacking

$$\{Y_{i,t}\}_{i=1}^N \text{ with } Y_t = (X_{1,t}, \dots, X_{N,t})' \in R^N.$$

Notice that $\{X_{i,t} : i = 1, \dots, N; t = 1, \dots, T\}$ is described by the sample realizations of N countries' variables at locations $\{S_{i,t} : i = 1, \dots, N; t = 1, \dots, T\}$.

D_t is the distance between country i and j defined by $D_t(i, j) = \|s_{i,t}, s_{j,t}\|$ with $\|\cdot\|$ describing the Euclidean norm. Thus 'distance' between countries are identified by their locations. Denoting the output growth of a country at t by y_t (Y_t denotes the level of output and the lower case denotes growth) and assuming that the growth of the country i at period $t+1$ depends not only on its growth at period t (that is home externalities), but also (non-parametrically) on the performance of its neighbours, say $y_{j,t}$ (that is spatial spillover effects/externalities), then the evolution of y_t (as comprised in the vector V_t) and the distance D_t jointly evolves as a first order Markov process which is represented by Eq. 3 as above. $A(D_t)$ in Eq. 3 is a $N \times N$ matrix of distance between the locations $s_{i,t}$ and $s_{j,t}$.

An imposing feature of the error term in Eq. 3 is that it is also a function of the distance between countries which identifies that as distance among countries rise, cross-correlation of the error term decreases. In Eq. 3 u_{t+1} is an *iid* sequence with $E(u_{t+1}) = 0$ and $V(u_{t+1}) = I_N$. The conditional mean of Y_t and variance matrix of the error term, ε_t , in Eq. 3 is a function of the distance, D_t . Details of the derivation of the conditional mean and variance of the error term can be found in Chen and Conley (2001). The conditional mean contains elements which describe dynamic spatial autocorrelation. In the figures which we will present in the subsequent section this is captured by f -function while the conditional variance is captured by γ -function. Both are exhibited as function of distances. The empirical specification of our model requires that distance between countries is represented in their relational space, not in the geographical space although a pre-defined geographic space is superimposed. The relational proximity between countries, in our case can be gauged by human capital accumulation dynamics. As will be apparent below, the distance matrix D_t in our case contains elements of the magnitudes of human capital appropriation in the production of Y_t among countries. The estimation of the above model is carried out by using Sieve estimator and cardinal B-spline approximations (see Chen and Conley, 2001 for details).

3. Empirical results

3.1 Data and distance measure

The empirical exercise is carried out for 15 Asian countries² for which consistent human capital data is available for the period 1970-2000. Physical capital stocks were calculated according to the perpetual inventory method as in Klenow and Rodriguez-Clare (1997). TFP growth is then calculated by the standard definition of output growth minus the growth of labor and capital. The global share of labor and capital in the Cobb-Douglas production technology has been assumed to be approximately (1/3) and (2/3) respectively where a constant returns to scale is allowed in the aggregate growth of all inputs together:

$$TFP_{it} = y_{it} - \frac{1}{3}k_{it} - \frac{2}{3}h_{it} \quad \dots \quad \text{Eq. 4}$$

where TFP_{it} is the log of total factor productivity, y_{it} is the log of real output, k_{it} is the log of the physical capital stock, and h_{it} is the log of the human capital.

To measure human capital, we have used IIASA-VID educational attainment data base (see Lutz et al., 2007). We have used level of education attainment (primary, secondary and tertiary) for three age groups, viz., 15-29, 30-49, and 50-64. TFP growth volatility is calculated by the standard deviation of estimates over time for each country. In the empirical illustration, we have used TFP estimate at their level, growth, and volatility to explicate basic differences in results. Two types of human capital *distance* measures have been used in this study. The first measure is based on secondary education attainment level of the age-structured population for total population. Using the average proportions of population in an age group (three age groups are considered: 15-29, 30-49 and 50-64) with completed secondary education or more, country locations $s_{i,t}$ are then identified by the ‘appropriation index’ of human capital in each country.

Distance between countries is then defined as follows. Two countries are close if the proportion of human capital in the age-structured population for two countries is same; distant, otherwise. Notice that we have superimposed a specific geographical proximity among countries, viz., the cluster of countries as in Asia which are joined by common borders and share affinities in socio-

² The list of countries are: Bangladesh, Cambodia, China, Hong Kong, India, Indonesia, Japan, Malaysia, Nepal, Pakistan, Philippines, Singapore, South Korea, Sri Lanka, and Thailand. The choice of countries are mainly guided by the data availability in human capital with explicit age dynamics.

economic and demographic patterns. The second measure of distance is based on country-specific elasticity estimates of human capital in the production process. For the purpose, we have estimated a Cobb-Douglas production function with human and physical capitals as two inputs of production. A panel estimation of economic growth with these two inputs has been performed and elasticity estimates of human capital have been recovered. Two countries can now be defined as close to each other if they utilize approximately same quantity of human capital in production. Note that proposition of this distance measure is purely based on the coverage of human capital's effects on production process of a country. While the former (the proportion based measure) induces productivity effects as the stock of human capital at each demographic level exerts varying productivity effects across country locations, the latter (elasticity based measure) induces a scale effect in the economies (affecting production through knowledge creation). Time non-varying distance is assumed for simplicity, which could be reasonable, given the slow paced demographic changes. Utilizing these 'human capital distance' metrics we estimate the spatial VAR model and show in terms of graphical presentation the effects of this distance on TFP growth volatility.

3.2 Discussion of results

Based on the model and data specifications described above, we demonstrate here the shapes of f -function (estimating the output co-movements) and γ -function (indicating residual covariance co-movements) with respect to the two distance metrics (in Figures 1, 2, and 3). The solid lines in these figures are our point estimates, where f (representing the shape of the conditional mean and spatial autocorrelation) is plotted against the distances, that is by the two measures of human capital (in the X-axis). The crosses represent 95 percent non-symmetric bootstrap confidence interval. Thus, the left hand side of each figure presents f estimates indicating the pattern of dynamic spatial autocorrelation due to variability of the distance measure, whereas the right hand side of the figure represents response of residual covariance structure due to variation in human capital at country levels.

In Figure 1 we present estimates for spatial variation of TFP level due to human capital distances (based on the proportion of human capital) among them. Spatial interdependence with respect to TFP growth and volatility and human capital distances are provided in Figures 2 and 3. Observe that although dynamic spatial autocorrelation is very small (Figure 1), they are nevertheless positive and significant on the average. The error covariance structure, represented by γ -function stabilizes around the zero line and tapers off fast as the human capital distance starts increasing. On the TFP growth aspect (Figure 2), cross-country growth, the dynamic spatial correlation appears to fluctuate around zero. However, clear pattern emerges, when spatial correlation in TFP

growth volatility is examined with respect to human capital distance (with respect to the elasticity measure) in Figure 3. We find that on the average the point estimate of dynamic spatial autocorrelation (that is averaged values of points on the f -curve is 0.284 with an estimated standard deviation of 0.15 indicating the significant (at approximately 5%) and positive spatial autocorrelation in TFP growth volatility among Asian countries. Spatial error covariance also depicts expected pattern: as distance among countries increases, spatial error covariance steadily falls (γ -function of Figure 3). In all the figures, a striking feature can be noticed regarding the correlation of TFP growth at higher human capital distances. This is indicative of what we may call a ‘spatial long-memory’ effect in the sense that even at higher distance co-movement pattern of TFP cannot be ruled out. An equivalent expression of this feature can be found in time series where a random variable can be correlated with its past values over a long period of time. Irrespective of its existence in time and space, the long-memory property implies the presence of non-convergent and most possibly non-stationary shock. In our case, it implies that a growth shock in the accumulation of human capital will have long-lasting impact on TFP co-movement.

Putting together, this confirms that countries’ TFP growth processes (level or growth volatility) are complementary and can be explained by the demography-led human capital accumulation, indicating the centrality of the latter in the generation of spatial TFP persistence. Since non-linear positive spatial correlation is observed for both distance metrics, we conjecture that both scale and productivity effects arising from the embedding of two distance measures in the regression (assuming feedback effect from demography to TFP growth via human capital accumulation) could be behind the non-linearity. The non-linear and positive dynamic spatial autocorrelation in TFP growth and volatility can also be interpreted as the possible presence of international business cycles.

4. Concluding remarks

To conclude, it is evident that TFP in Asian countries are dynamically and spatially correlated. That is the changes in TFP at location i and at time t will have significant bearing on location j with forward and/or backward time lags. We observe that the dynamic spatial autocorrelation of TFP across Asian countries is a result of the rate of age-structured human capital accumulation which defines *prima facie* the extent of non-linearity (the neighborhood structure) on TFP and thus on how such dynamic spatial correlations are going to shape up the growth momentum in Asian economies. The empirical evidence in this article suggests that cooperation in human capital policy and countering TFP growth volatility would prove beneficial for maximizing aggregate welfare. It is also an illustration of the main achievement of cliometrics in the recent years, i.e. to slowly but surely establish a solid set of economic analyses

of historical evolution by means of measurement and theory. Nothing can now replace rigorous statistical and econometric analysis based on systematically ordered data. Impressionistic judgements supported by doubtful figures and fallacious methods and whose inadequacies are padded by subjective impressions have now lost all credit with serious, honest scientists. Economic history in particular should cease to be a story illustrating with facts the material life during different periods and become a systematic attempt to provide answers to specific questions. By extension, the more the quest for facts is dominated by the conception of the problems, the more research work will address what forms the true function of economic history in the social sciences. This change of intellectual orientation, of cliometric reformulation can thus reach associated disciplines (law, sociology, political science, geography, etc.) and engender similar changes. Indeed, the most vigorous new trend in the social sciences is without a doubt the preoccupation with quantitative and theoretical aspects. It is the feature that best distinguishes the concepts of our decade from those current from after World War 2 until the 1980s. Everybody is ready to agree to this—even the most literary of our colleagues. There is nothing surprising about this interest. One of the characteristic features of today's younger generation is most certainly that its intellectual training is much more deeply marked by science and the scientific spirit than that of the generations that preceded us. It is therefore not surprising that young scientists should have lost patience with regard to the tentative approach of traditional historiography and have sought to build their work on foundations that are less artisanal. The social sciences are thus becoming much more elaborate in the technical respect and it is difficult to believe that a reversal of the trend might occur. However, it is clear that many scientists—perhaps the majority—have not yet accepted the new trends aimed at using more elaborate methodology and clear concepts conforming to new norms in order to develop a truly scientific social science.

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Figure 1: Conditional mean (in the left) and covariance (in the right) functions based on age-structured human capital proportions and TFP level

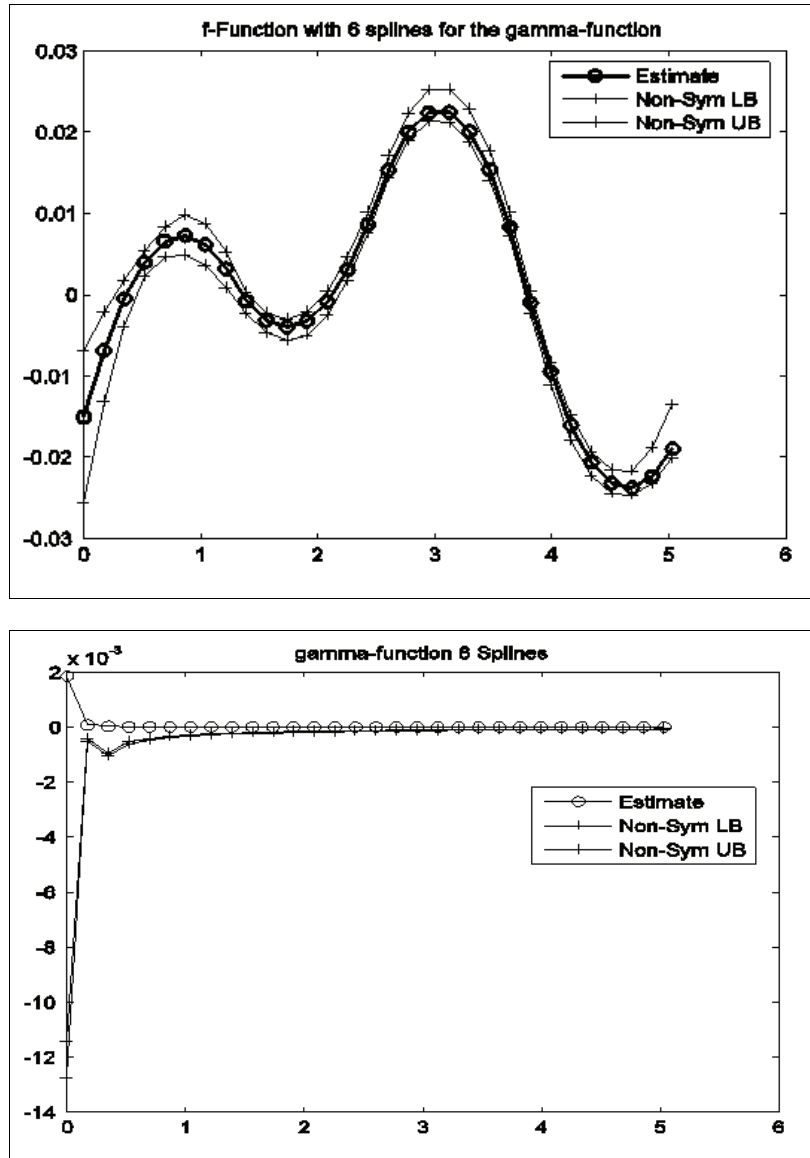


Figure 2: Conditional mean (in the left) and covariance (in the right) functions based on elasticity of human capital and TFP growth

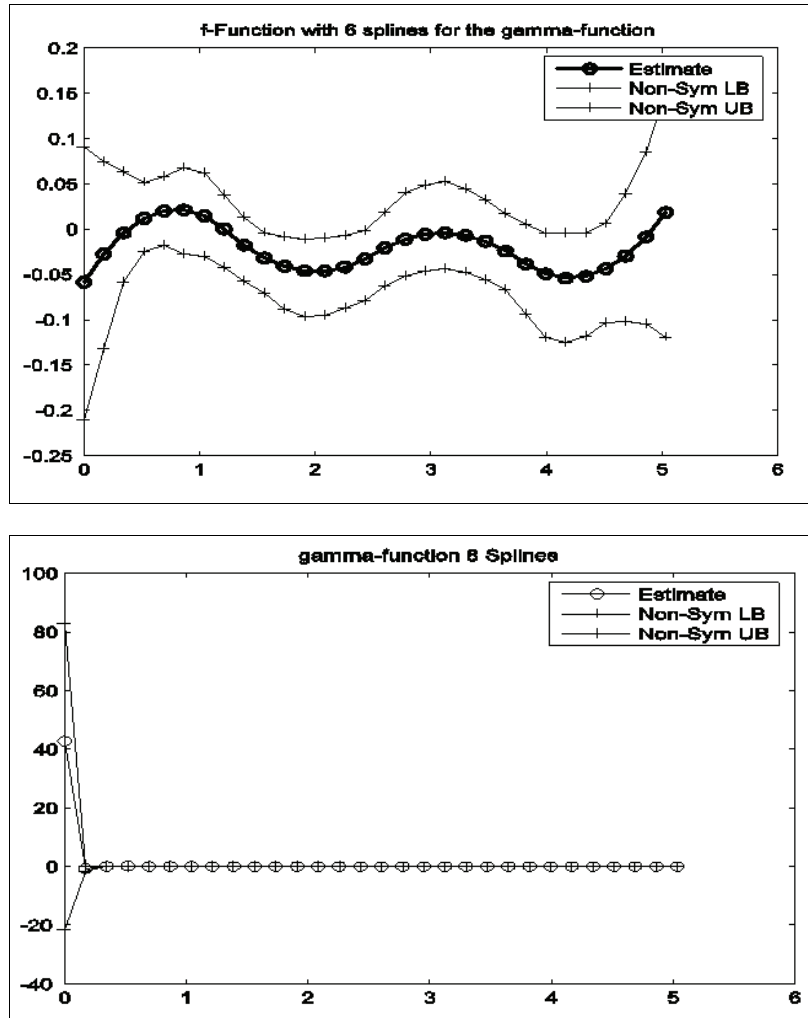


Figure 3: Conditional mean (in the left) and covariance (in the right) functions based on elasticity of human capital and TFP growth volatility

